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Load quantification and effect evaluation of urban non-point source pollution in the Licun River based on SWAT model

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ABSTRACT

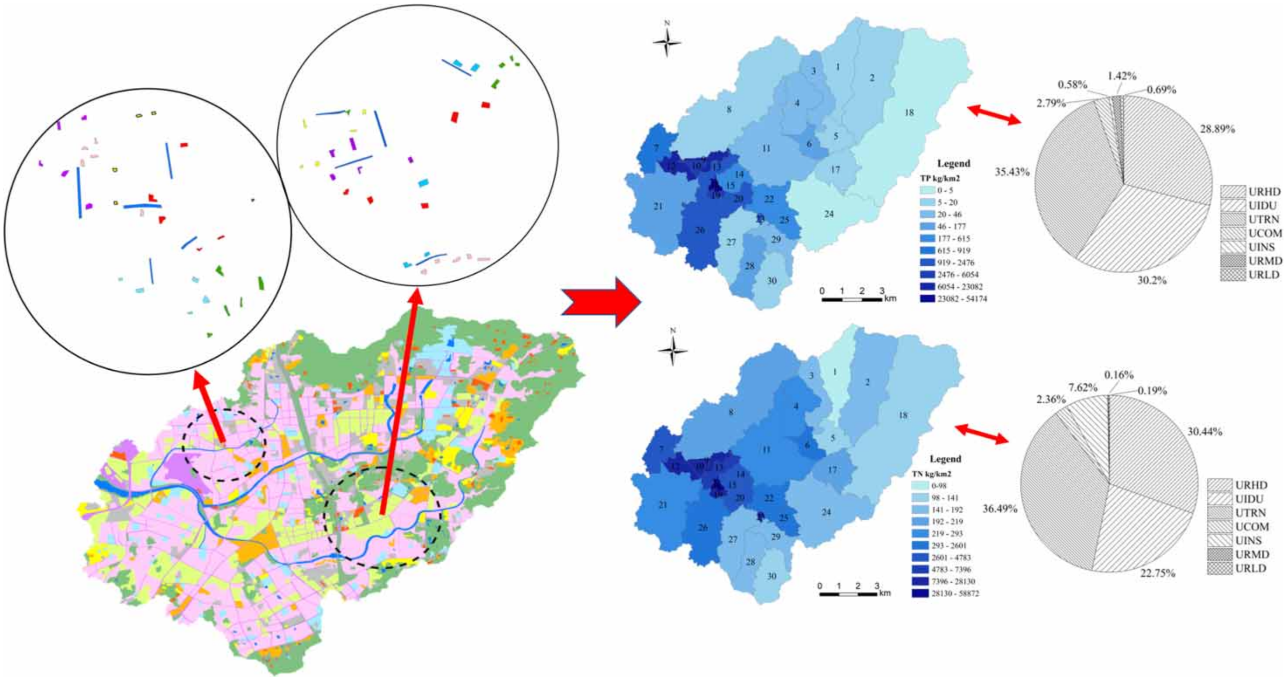
With the gradual control of point source pollution, the impact of urban nonpoint source pollution on river water quality is becoming more prominent. Regarding the current problem that nonpoint source pollution loads in urban basins are difficult to quantify and the impact on water quality is difficult to analyze, the Licun River basin in Qingdao was selected as the research object. Through the field survey and surface accumulation sampling analysis of the basin, the evaluation model of urban nonpoint source pollution was constructed by revising the land type data of the basin and the urban database of the SWAT model. The results showed that concentration of nitrate in precipitation was most sensitive to the simulation of nitrogen loading; organic P in baseflow was most sensitive to the simulation of phosphorus loading. The Nash–Sutcliffe efficiency coefficient (E_{NS}) and the coefficients of determination (R^2) of the SWAT model for runoff, total phosphorus (TP), and total nitrogen (TN) in the simulation validation period meet the model requirements,indicating a good model fit. In addition, the spatial and temporal distribution characteristics of urban nonpoint source pollution of TN and TP in 2021 were analyzed. In July, rainfall-runoff from the Licun River basin was the most polluted.

Key words: impact assessment, load quantification, SWAT model, urban nonpoint source pollution

HIGHLIGHTS

- High-accuracy simulation of urban nonpoint source pollution in small-scale basins.
- Revising the land type data of the basin and modifying the model's town database.
- Realize quantification and impact analysis of urban nonpoint source pollution load.

GRAPHICAL ABSTRACT



1. INTRODUCTION

In urban areas of China, the large percentage of impervious areas, the complexity of production activities, and the variety of pollution sources have led to serious pollution of urban rivers. Urban nonpoint source pollution is the second-largest source of nonpoint source pollution after agricultural nonpoint source pollution (Zhang *et al.* 2011; Cheng *et al.* 2017). In recent years, with the improvement of sewage collection, interception systems, and effluent standards of the sewage treatment plants in urban areas of China, point source pollution has been gradually controlled. On the other hand, the impact of urban nonpoint source pollution on river water quality is becoming more prominent. Therefore, it is urgent to study the load quantification and impact of urban river nonpoint source pollution, thus providing data support for improving urban river water quality.

At present, the load quantification of urban surface pollution is mostly estimated using empirical formulas, and there is a lack of a more accurate load quantification method. With the massive development of distributed hydrological models (e.g., SWAT, HSPF, AnnAGNPS models) (Radcliffe & Cabrera 2006; He *et al.* 2020; Marin *et al.* 2020), the high-accuracy simulation of agricultural nonpoint source pollution loads in large-scale basins has been achieved. However, there is a lack of research on applying models for load quantification and impact analysis of urban nonpoint source pollution in small-scale basins of urban rivers.

The Licun River basin in Qingdao is a typical urban river catchment area. At present, the nitrogen and phosphorus in the effluent of the wastewater treatment plant in the basin of the Licun River have reached the IV standard for surface water, and the sewage interception system in this region has become more comprehensive. Consequently, urban nonpoint source pollution has become the primary type of pollution affecting the water quality of the Licun River. Therefore, the Licun River basin in Qingdao was selected as the study object, and the SWAT model was used for simulation analysis. Through the field survey and surface accumulation sampling, the acquired land use data and the urban database of the model were revised, achieving the urban nonpoint source pollution load quantification and impact analysis of the Licun River basin. This study can provide a reference for analyzing urban nonpoint source pollution of similar urban rivers in China.

2. GENERAL INFORMATION OF THE STUDY AREA

The Licun River basin is located in Qingdao, Shandong Province, China, with a basin area of 137 km^2. It is in the north temperate monsoon climate region, influenced by the southeast monsoon of the ocean, and has significant maritime climate characteristics. The average annual temperature of the basin is 12.7 °C, the average annual rainfall is 662.1 mm, and the rainfall is unevenly distributed throughout the year, with spring, summer, autumn, and winter precipitation accounting for 17, 57, 21, and 5%, respectively. In addition to the mainstream of the Licun River, the basin also contains the Zhangcun River, the Dacun River, the Shuiqinggou River, and the Jinshui River. Among them, the mainstream of the Licun River has a recycled water purification plant for the Expo, a wastewater treatment plant for the Licun River, the Wuyang Road water replenishment site, and the triangle water replenishment site. Tributary Zhangcun River has a water quality purification plant along the river and a water replenishment site for No.2 Tsingtao Brewery, which is the primary point source input and replenishment source for the Licun River basin. The geographical location of the Licun River basin and the distribution of the water system are shown in Figure 1.

3. RESEARCH METHOD AND DATA PROCESSING

3.1. Research method

The SWAT model is commonly used for the analysis of nonpoint source pollution. It includes modules for rainfall simulation, sink production, and diffusion of river water quality (Ding & Zheng 2004; Radcliffe & Cabrera 2006). Because of its pesticide/insecticide module and the agricultural management module, the SWAT model is often used to simulate agricultural nonpoint source pollution in basins and is rarely used for urban nonpoint source pollution studies. According to the *ArcSWAT Interface for SWAT2009: User's Guide* (Winchell 2012) and the *SWAT* Input/*Output File Documentation Version 2009* (Arnold *et al.* 2011), it was found that the SWAT model for versions 2009 and above already has an urban database. The basin land use data and urban database have been improved, enabling the simulation of urban nonpoint source pollution in the basin with the SWAT model. The key parameters of the SWAT model urban database (Arnold *et al.* 2011; Abdelwahab *et al.* 2018) are shown in Table 1.

In this study, DIRTMX, TNCONC, TPCONC, and TNO3CONC values were determined by monitoring and analyzing the surface deposits in the study area. Currently, two primary surface accumulation sampling methods are commonly used: the dry and wet sampling methods (Li *et al.* 2015). According to the tools used, the dry sampling method can be subdivided into

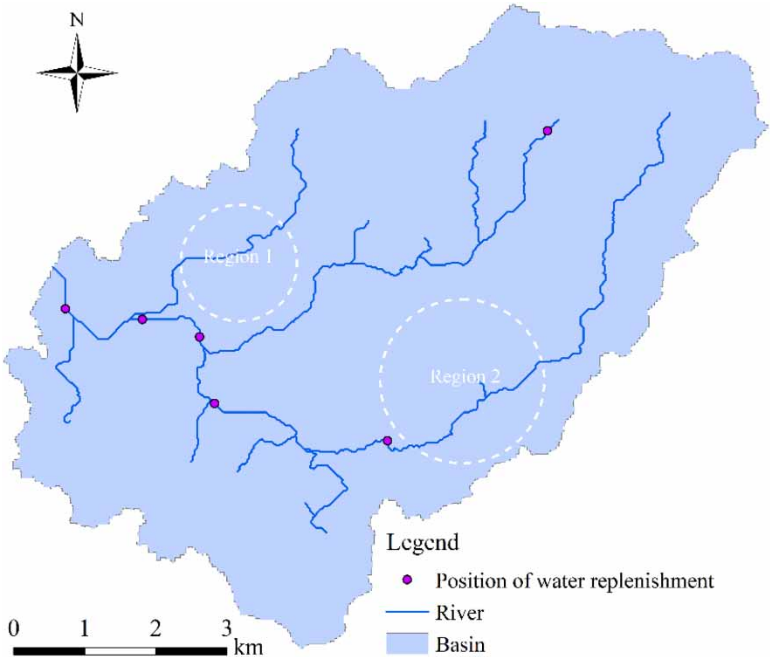


Figure 1 | Distribution of water systems in the Licun River basin.

Table 1 | Parameters of SWAT model urban database

Parameters	Meanings
FIMP	Fraction of total impervious area in urban land
FCIMP	The proportion of impervious areas with direct hydraulic connections in urban land types
CURBDEN	Curb length density in urban land type (km/ha)
URBCOEF	The wash-off coefficient for removal of constituents from the impervious area (mm^{-1})
DIRTMX	The maximum amount of solids allowed to build up on impervious areas (kg/curb km)
THALF	Number of days required to accumulate solids from 0 to 1/2 DIRTMX in impervious zone (day)
TNCONC	The concentration of total nitrogen in suspended solid load from impervious areas (mg N/kg sediment)
TPCONC	The concentration of total phosphorus in suspended solid load from impervious areas (mg P/kg sediment)
TNO3CONC	The concentration of nitrate in suspended solid load from impervious areas (mg NO_3-N/kg sediment)
URBCN2	Curve number for an impervious fraction

the brush or broom sweeping method and the vacuum sampling method using a vacuum cleaner. In the wet sampling method, the ground is first cleaned using deionized water, and the mud-water mixture is absorbed through a vacuum cleaner (Chang *et al.* 2007). In this study, dry sampling of the study area was carried out using a wool brush and an 800 W German Kahl vacuum cleaner, and the sampling process was as follows:

(1) In the selected sampling region, sampling points are laid along with the street side stones. According to the area of the sampling region, the number of sampling points was determined, with no less than five points in each region. A self-made sampling frame of 1.0 m × 1.0 m was placed at the sampling site to collect the samples in the frame.
(2) During sampling, a vacuum cleaner was first used to collect dust from the frame horizontally and vertically. Then, the brush was used to sweep the surface of the frame back and forth, removing the particles attached to the surface. Finally, the vacuum cleaner was used again to collect the dust from the frame with three to five repetitions.
(3) The surface dust collected in the dust collection bag of the vacuum cleaner was moved into a sterile sampling bag and labeled.

The previous study has shown that surface pollutants eventually saturate with the drought duration before rain (Kim *et al.* 2006; Chang *et al.* 2007). Through the study of the urban surface pollutant accumulation process, Gastaldini & Silva (2013) found that the surface pollutant content reached saturation when the duration of drought before the rain was more than 7 days. Therefore, this study chose to collect mixed samples within a region under windless conditions with a clear duration of 7 days or more before the rain, avoiding the cleaning time. In this study, the cumulative monitoring points of surface pollutants in the Licun River basin were mainly concentrated in two regions. The sampling area covered 17 km^2, including seven types of urban lands in the Licun River basin (Figure 2): high-density residential land (URHD), industrial land (UIDU), transportation land (UTRN), commercial land (UCOM), institutional services land (UINS), medium density residential land (URMD), and low-density residential land (URLD). Surface sediments from each type of urban land within each area were sampled, five times for each type of land. Therefore, the total number of sampling areas for the seven types of urban land in the two overall areas was 70. To determine the values of DIRTMX, TNCONC, TPCONC, and TNO3CONC for the 7 urban land types in the Licun River, 11 cumulative samplings and monitoring of surface pollutants were conducted from September 2020 to April 2021. A total of 350 samples were obtained during the rainy season with high rainfall and the dry season with low rainfall.

3.2. Data processing

According to Cheng *et al.* (2017), urban rainfall-runoff pollution is mainly caused by fine dust with particles ranging from 50 to 1,000 μm. Therefore, the collected surface accumulations were sieved using metal sieves in this study. Samples of particles smaller than 1 mm are weighed, recorded, and then repeatedly bumped to achieve a uniform distribution of different-sized particles. Each sample was dissolved in 1 L of deionized water with 5 g, and the total nitrogen (TN), nitrate-nitrogen, and total phosphorus (TP) of the mixed water samples were measured. In addition, three sets of parallel samples were set up for each group of samples.

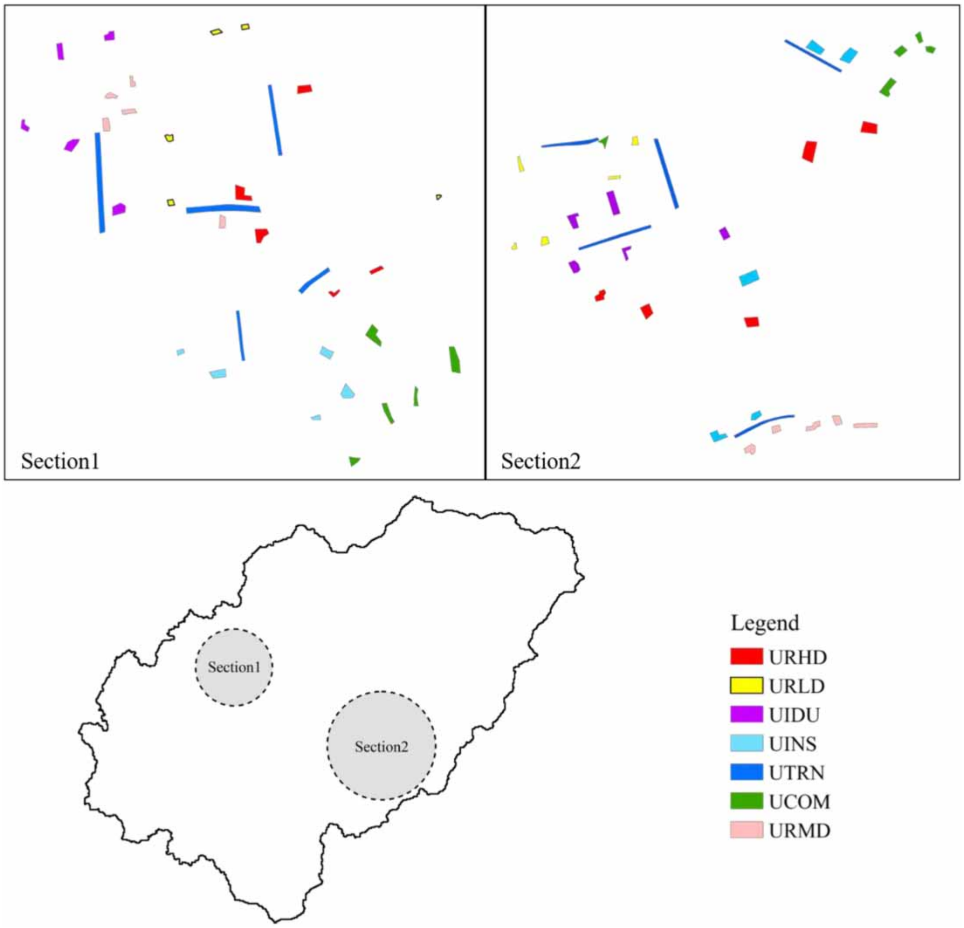


Figure 2 | Distribution of surface dust sampling areas.

This study uses a combination of basic data collection and on-site monitoring analysis to obtain the relevant data required for SWAT model construction. Data types can be divided into spatial data and surface observation data. Unlike previous studies, there is less agricultural land and larger urban land in the Licun River basin. Therefore, agricultural management data were not collected during data collection. The data and basic information required for SWAT model construction are shown in Table 2.

Table 2 | Data sources and basic information required for SWAT model construction

Data type	Name	Source	Description
Spatial data	Basin topography	Geospatial Date Cloud	DEM raster data at 30 m resolution
	Basin land types	Resource and Environment Science and Date Center	Vector data of 1 km × 1 km
	Basin soil type		Vector data of 1:1,000,000
Surface observation data	Meteorological data	Qingdao Meteorological Bureau	Daily data for 2018–2021
	Point source data	Qingdao Municipal Bureau of Ecology and Environment	Daily data on water quantity and quality at replenishment sites from 2018–2021
	Water quality data of control section		Monthly cross-sectional data of Shengli Bridge in 2020 and 2021
	Water data from hydrological stations	Qingdao Hydrographic Bureau	Daily data of Licun hydrological station from 2018 to 2021
	Soil property data	Chinese soil database, SPAW software (Liu *et al.* (2009))	Soil property database with updated models
	Property data of urban land type	On-site monitoring studies	Urban database with updated models

To facilitate the construction of the model, the spatial data must be pre-processed. Figure 3 shows the raw spatial data collected in this study and the processed data.

In this study, the spatio-temporal uncertainty adaptation algorithm SUFI-2 is selected for model calibration and parameter rate determination. The method is a global sensitivity analysis depending on a multiple regression system between the value of the objective function and the parameters generated by the Latin hypercube. Its expression is given in the following equation (Changxing *et al.* 2018):

$$\xi = \alpha + \sum_{i=1}^{m} \beta_i \cdot b_i \tag{1}$$

The relative significance of each parameter b_i is determined by t-test; the sensitivity of each parameter is measured by the algorithm output parameter t_{stat}, with larger absolute values indicating high sensitivities.

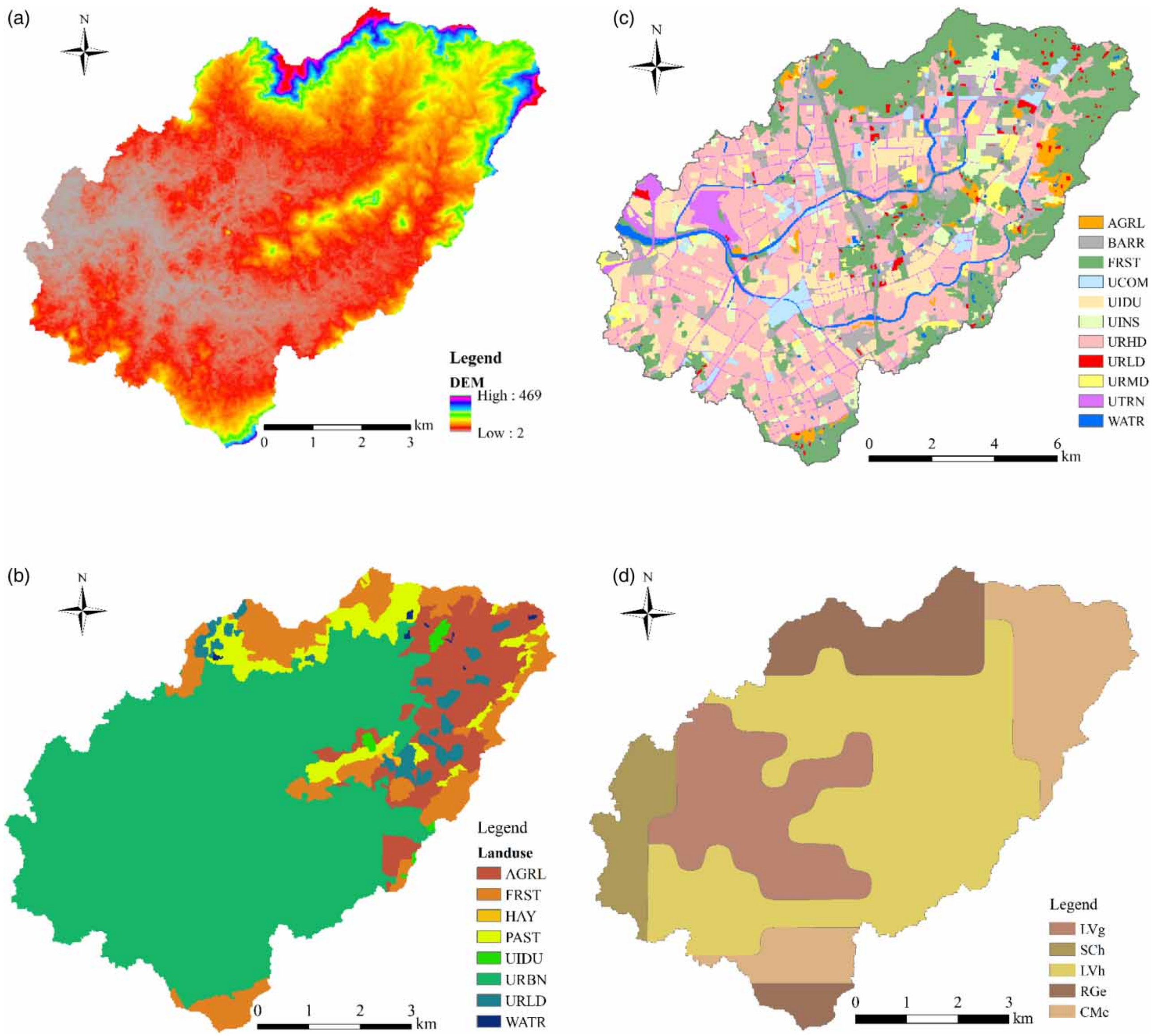


Figure 3 | Raw spatial data and processed data. (a) Processed DEM data. (b) Raw land type data. (c) Reclassified land type data. (d) Soil type data.

For the validation of the simulation results of the SWAT model, this study uses the coefficient of determination R^2 and the Nash–Sutcliffe efficiency coefficient E_{NS} for a comprehensive evaluation (Ierodiaconou *et al.* 2005), which is calculated in Equations (2) and (3). When $E_{\mathrm{NS}} \geq 0.5$ and $R^2 \geq 0.6$, the model is well fitted (Wang *et al.* 2010).

$$E_{\mathrm{NS}} = 1 - \frac{\sum_{i=1}^{T} (Q_0^t - Q_m^t)^2}{\sum_{i=1}^{T} (Q_0^t - \overline{Q_0})^2} \tag{2}$$

where Q_0^t is the observed value at moment t; Q_m^t is the simulated value at moment t; $\overline{Q_0}$ is the mean of the observed values; E_{NS} is taken from negative infinity to 1, with E_{NS} close to 1 indicating a good fit and high model credibility.

$$R^2 = \left| \frac{\sum_{i=1}^{T} (Q_0^t - \overline{Q_0}) \cdot \sum_{i=1}^{T} (Q_m^t - \overline{Q_m})}{\sqrt{\sum_{i=1}^{T} (Q_0^t - \overline{Q_0})} \cdot \sqrt{\sum_{i=1}^{T} (Q_m^t - \overline{Q_m})}} \right| \tag{3}$$

where $\overline{Q_m}$ is the mean of the simulated values; the value of R^2 ranges from 0 to 1, with R^2 value closer to 1 representing a higher degree of model fit.

4. RESULTS AND ANALYSIS

4.1. Construction of urban database

The sampling study of the surface accumulation of the urban land types in the Licun River basin was conducted. Afterward, based on the relevant parameter ranges provided in the *SWAT* Input/*Output File Documentation Version 2009* (Winchell 2012) and the existing research results (Zhang *et al.* 2021), a SWAT model urban database of the Licun River basin was constructed. Among the parameters, FIMP, FCIMP, and CURBDEN were determined from field investigations, DIRTMX, TNCONC, TPCONC, and TNO3CONC were determined from surface sediment examinations, and URBCOEF, THALF, and URBCN2 were determined by referring to the *SWAT* Input/*Output File Documentation Version 2009* (Winchell 2012) with the calibration studies of Feng-Jiao & Tian-Hong (2012) and Zhang *et al.* (2022) on CN values in the Guanlan River in Shenzhen and the Licun River basin in Qingdao.

As shown in Figure 4, the mean maximum value of DIRTMX of surface sediment of seven urban land types in the Licun River basin is 28.84 kg/km for URLD, and the minimum value is 6.09 kg/km for UINS. The mean maximum value of TNCONC is 83.29×10^3 mg/kg for URHD, and the minimum value is 15.32×10^3 mg/kg for UINS. The maximum mean value of TNO3CONC is 0.53×10^3 mg/kg for UINS, and the minimum value is 0.14×10^3 mg/kg for UINS. The maximum mean value of TPCONC is 7.96×10^3 mg/kg for URHD, and the minimum value is 1.43×10^3 mg/kg for URMD. The initial values for the key parameters of the established SWAT model urban database are shown in Table 3. The measured values of DIRTMX, TNCONC, TNO3CONC, and TPCONC of the SWAT model urban database in the Licun River basin differ significantly from the reference values provided by the SWAT model. This result is because the default parameter values of the SWAT model urban database are based on relevant studies in urban construction areas in the United States, which differ significantly from the current situation of urban nonpoint source pollution in China. Therefore, when constructing the SWAT model to study urban nonpoint source pollution in the basin, the parameter values in the SWAT model urban database must be modified according to local characteristics.

4.2. Model calibration and validation

The river conditions of the Licun River basin generated by the SWAT model are consistent with the actual ones, with 30 subbasins divided by the model. Based on the characteristics of the Licun River basin, the soil type area threshold set in this study is 5%, the land type area threshold is 5%, and the slope is divided into three levels: <7, 7 to 13, and >13%, with a total of 233 HRUs. Sensitivity analysis of the parameters was performed by SUIF-2 to identify the 10 parameters in the basin that are most sensitive to runoff, nitrogen loads, and phosphorus loads. Among these parameters, the bank flow constant (ALPHA_BNK), the overland flow Manning coefficient (OV_N), the Manning coefficient (CH_N2), and the saturation permeability coefficient

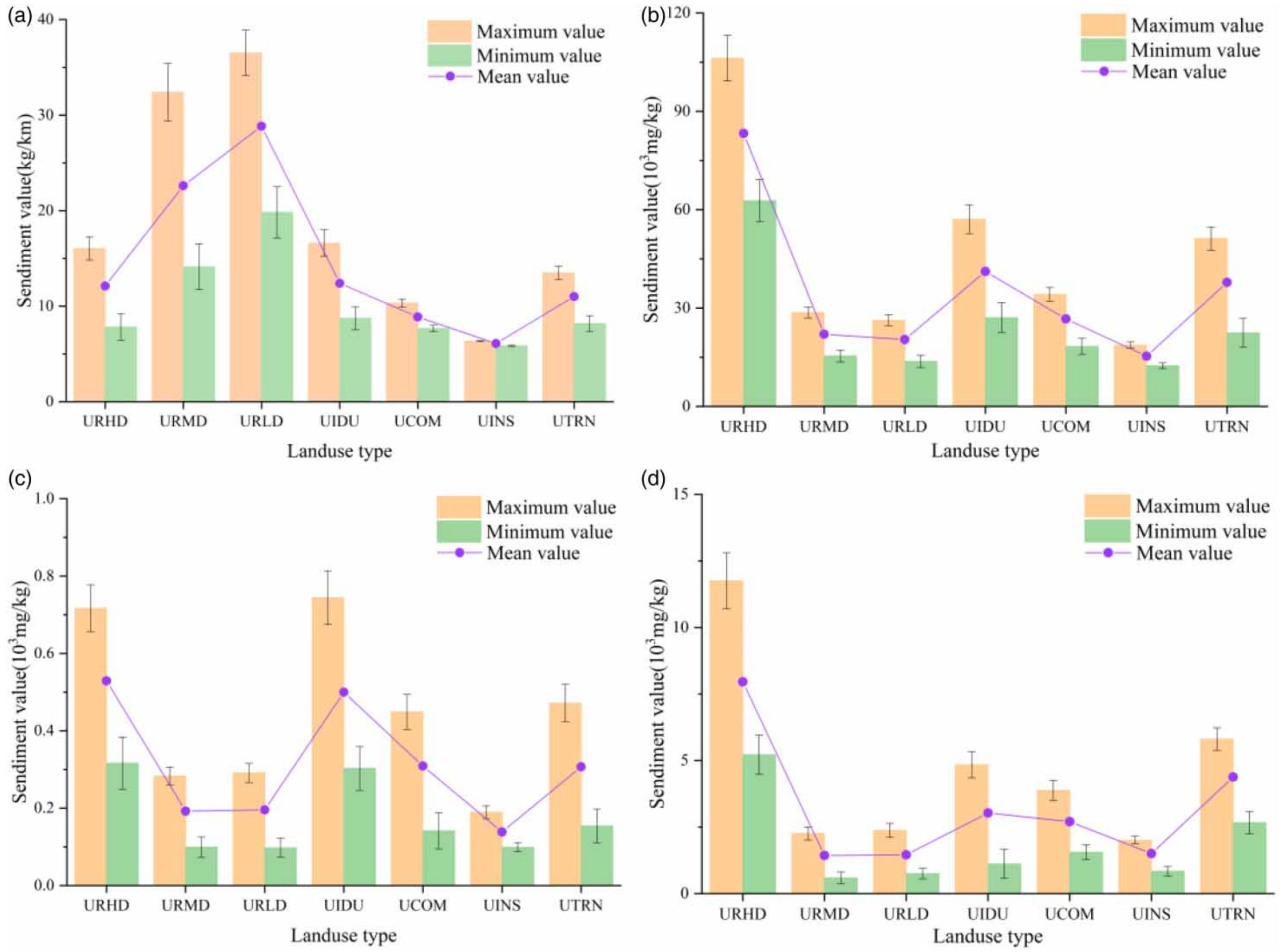


Figure 4 | Results of surface sediment monitoring for urban land types of the Licun River basin. (a) DIRTMX (b) TNCONC (c) TNO3CONC (d) TPCONC.

Table 3 | Initial values of key parameters in the SWAT model urban database of the Licun River basin

Parameters	URHD	URMD	URLD	UIDU	UCOM	UINS	UTRN
FIMP	0.91	0.56	0.39	0.75	0.93	0.43	0.89
FCIMP	0.8	0.48	0.3	0.71	0.82	0.34	0.88
CURBDEN (km/km^2)	35	31	25	16	27	21	14
URBCOEF (mm^{-1})	0.15	0.15	0.15	0.15	0.15	0.15	0.15
DIRTMX (kg/km)	11.94	23.27	28.17	12.66	9.00	6.09	10.84
THALF (d)	0.85	0.85	0.85	2.45	1.7	3.95	3.95
TNCONC (10^3 mg/kg)	81.38	20.34	18.11	39.87	28.81	16.54	38.84
TPCONC (10^3 mg/kg)	9.28	1.74	1.53	3.91	3.59	1.56	4.67
TNO3CONC (10^3 mg/kg)	0.61	0.20	0.15	0.53	0.29	0.16	0.32
URBCN2	94	94	94	94	94	94	94

(SOL_K) are the most sensitive ones for the simulation of runoff. In addition, nitrate concentration in precipitation (RCN_SUB_BSN), nitrogen fixation coefficient (FIXCO), biological rate of ammonium conversion of organic nitrogen (BC3), and biological rate of nitrite nitrification (BC2) were the most sensitive to the simulation of TN; organic P in baseflow

(LAT_ORGP), organic P enrichment ratio (ERORGP), and phosphorus sorption coefficient (PSP) were the most sensitive to the simulation of TP (Figure 5). In this study, water quantity data from the Licun hydrological station and water quality data of the Shengli Bridge cross-section for the years 2018–2021 in the Licun River basin were collected. Based on the collected data, the runoff and water quality of the Licun hydrological station and Shengli Bridge cross-section were calibrated and validated. The simulation step was set to month, and $E_{NS} \geq 0.5$ and $R^2 \geq 0.6$ are used as the criteria to judge the end of the run.

The analysis results of simulated and measured values of monthly runoff, TP load, and TN load are shown in Figure 6. The E_{NS} for the runoff calibration period is 0.75, and the R^2 is 0.76; the E_{NS} for the validation period is 0.71, and the R^2 is 0.73. Moreover, the E_{NS} for the calibration periods of TN load and TP load are 0.81 and 0.81, respectively, and the R^2 are 0.81 and 0.84, respectively; the E_{NS} for the validation periods of monthly TN load and TP load are 0.83 and 0.74, respectively, and the R^2 are 0.83 and 0.77, respectively. It can be seen that the model simulation results have a high degree of confidence and fit well with the actual values.

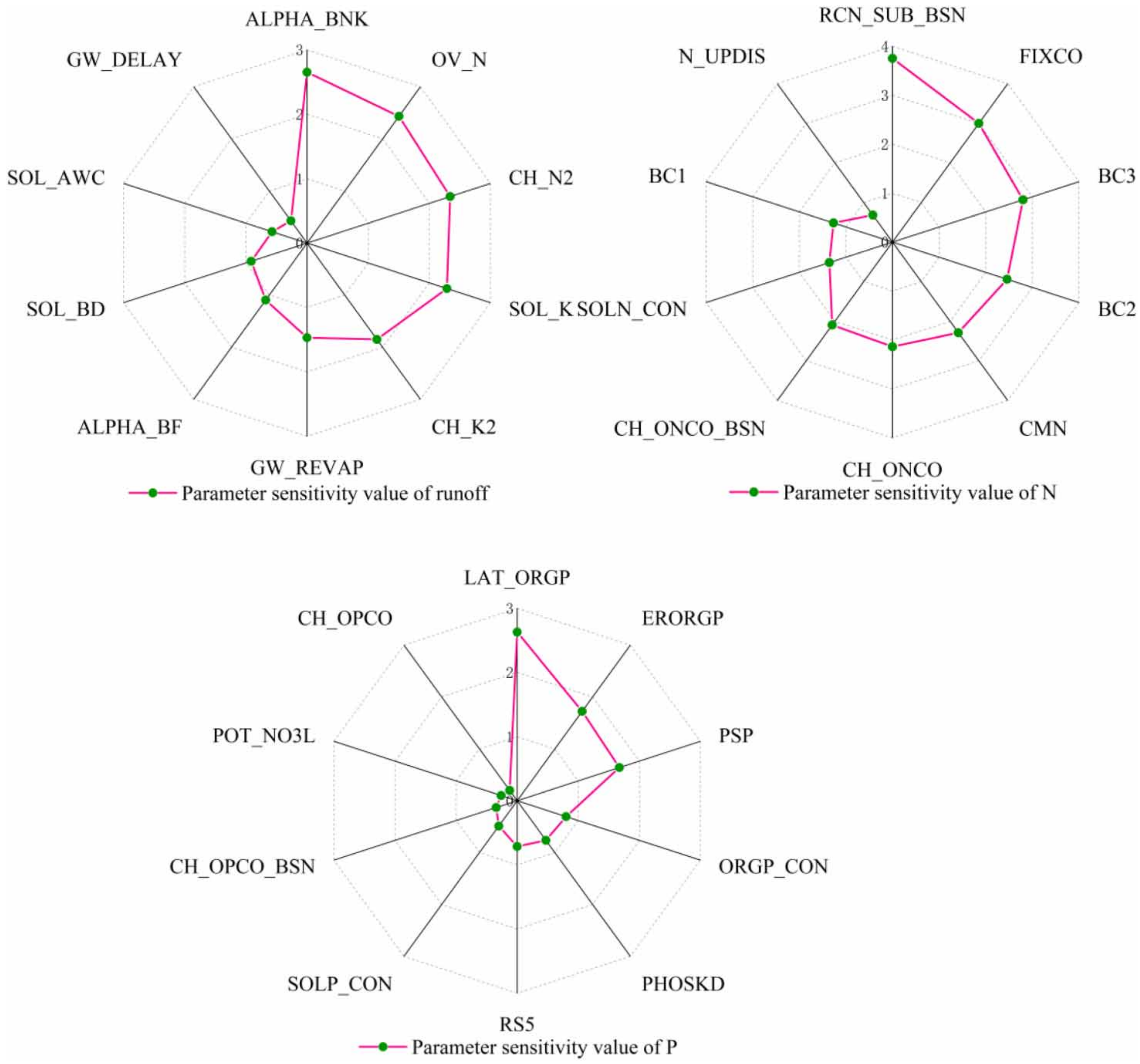


Figure 5 | Analysis results of parameter sensitivity in the study area.

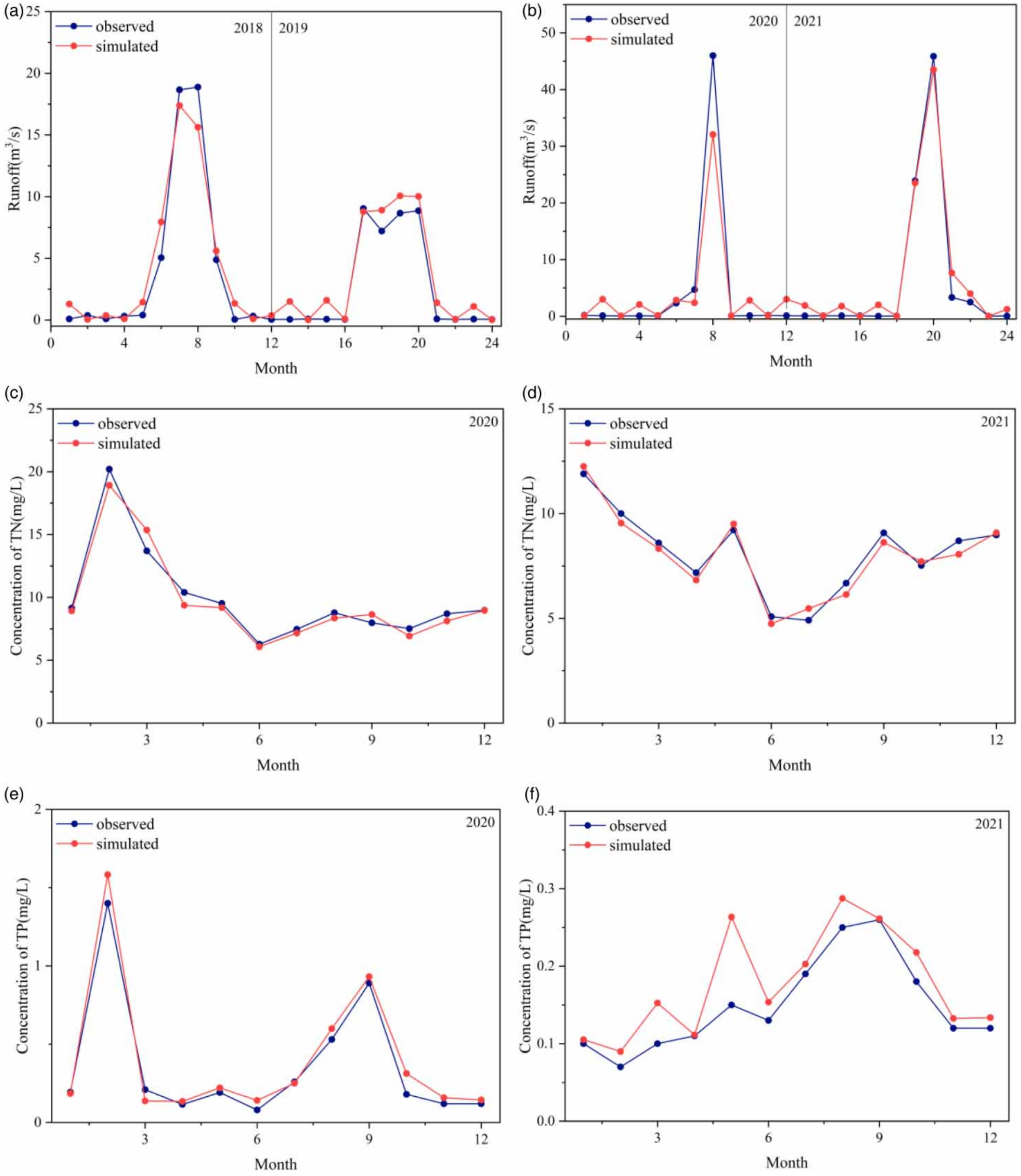


Figure 6 | Simulation of runoff, TN, and TP by SWAT model. (a) Runoff calibration period. (b) Runoff validation period. (c) TN calibration period. (d) TN verification period. (e) TP calibration period. (f) TP verification period.

4.3. Spatial distribution characteristics of urban nonpoint source pollution in the basin

The spatial distribution characteristics of the output load of nonpoint source pollution per unit area of TN and TP in the Licun River basin in 2021 and the contribution rate of the output nonpoint source pollution load of each type of the functional area to the total load were analyzed by the SWAT model (Figures 7 and 8). In 2021, the nonpoint source pollution output load of the TN unit area in the Licun River basin is highest in sub-basins 16, 9, 23, and 12, ranging from 21,757.97 to 58,871.16 kg/km^2. The nonpoint source pollution output load per unit area of TP is highest in sub-basins 16, 9, 12, and 19, ranging from 6,054.30 to 54,173.85 kg/km^2. Among the seven urban land types in the Licun River basin, the contribution of TN and TP

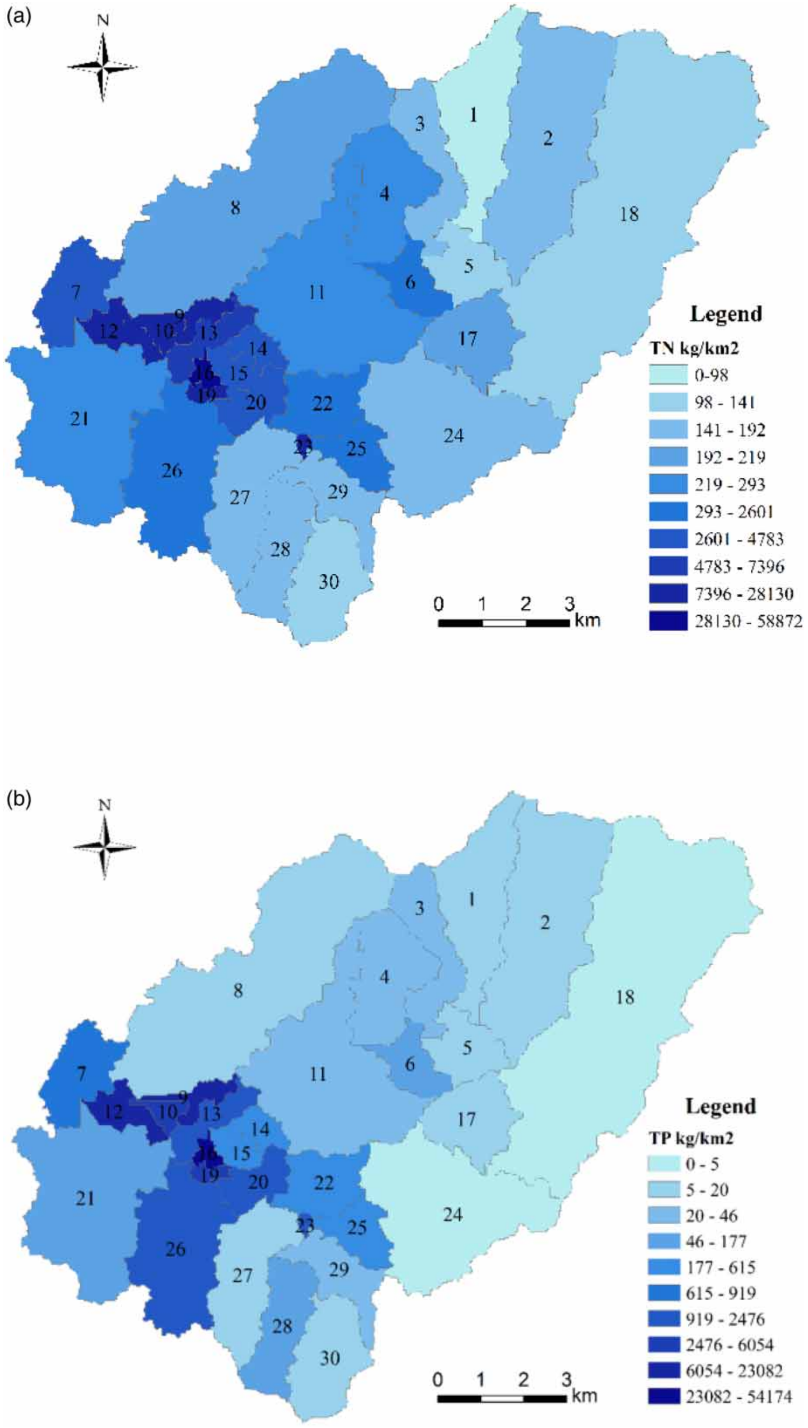


Figure 7 | Spatial distribution of annual output load of nonpoint source pollution per unit area of TN and TP in the Licun River basin in 2021. (a) TN output load per unit area. (b) TP output load per unit area.

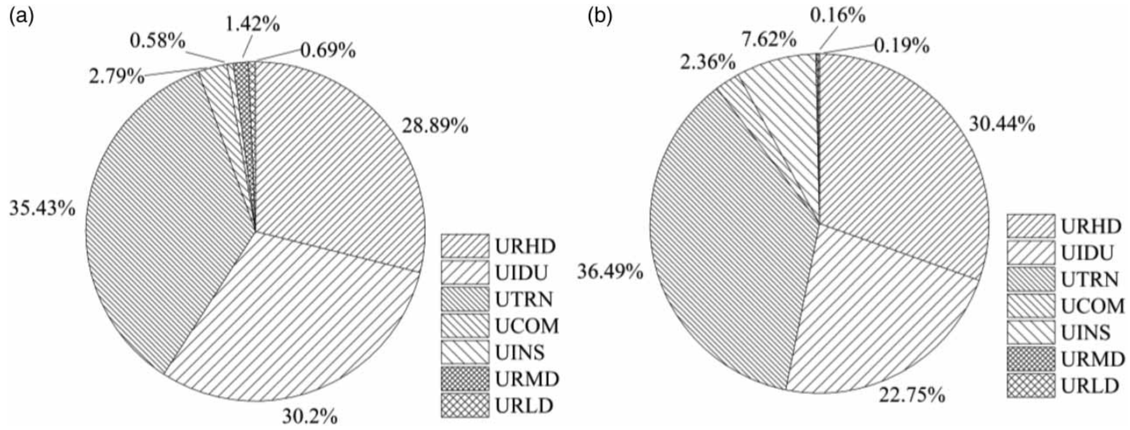


Figure 8 | TN (a) and TP (b) contribution rate of nonpoint source pollution loads from land types in the Licun River basin in 2021.

load from UTRN is the highest, accounting for 34.61 and 35.20%, respectively; the contribution of TN load from UINS is the lowest, accounting for 0.57%; the contribution of TP load from URMD is the lowest, accounting for 0.15%.

4.4. Characteristics of the temporal distribution of urban nonpoint source pollution in the basin

The main input point source of the Licun River basin is the tailwater from the sewage treatment plants built along the mainstream. By using the collected daily variation data of tailwater quantity and water quality of each water purification plant in the Licun River basin in 2021, a point source input database of the SWAT model was established. Based on this model, the contribution of TN load and TP load to the urban nonpoint source pollution water bodies in the Licun River basin in 2021 was analyzed (Figure 9). In 2021, the TN load and TP load from rainfall-runoff pollution in the Licun River basin from April to September were higher than those from January to March and from October to December, and the rainfall-runoff pollution in the Licun River basin was the most serious in July, with TN load and TP load of 33.91 t and 21.05 t, respectively.

5. CONCLUSION

By sampling and monitoring the surface sediments of seven types of urban land in the Licun River basin, the SWAT model urban database was constructed, and the parameters were calibrated in a localized manner. Sensitivity analysis of the

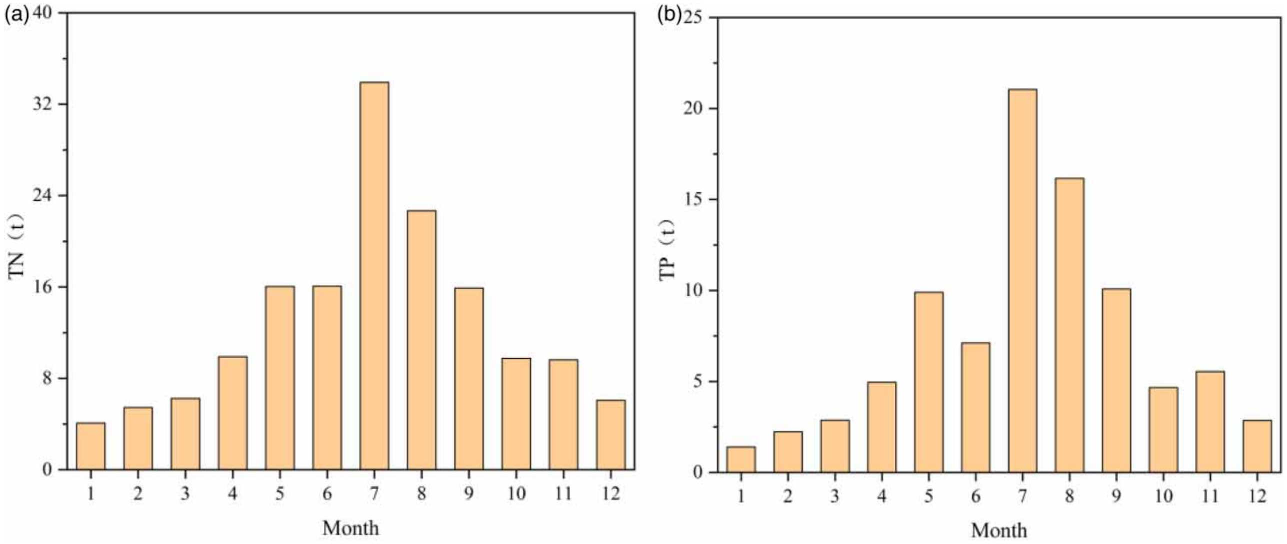


Figure 9 | TN (a) and TP (b) loads of urban nonpoint source pollution in the Licun River basin in 2021.

parameters showed that: The parameters RCN_SUB_BSN, FIXCO, and BC3 are most sensitive to the simulation of monthly TN load, and the parameters LAT_ORGP, ERORGP, and PSP are most sensitive to the simulation of monthly TP load. In addition, the E_{NS} and the R^2 of the constructed SWAT model for the simulation validation period of runoff, TP load, and TN load of the control section suggest an excellent fit to the actual values and high confidence of the simulation results.

By using the corrected SWAT model, the spatial and temporal distribution characteristic analysis of TN and TP in the Licun River basin in 2021 revealed that the highest spatial distribution of TN and TP unit area annual output loads are 58,871.16 and 54,173.85 kg/km^2, respectively. Among seven urban land types, the contribution of TN and TP load from UTRN is the highest, accounting for 34.61 and 35.20%, respectively; the contribution of TN load from UINS is the lowest, accounting for 0.57%; the contribution of TP load from URMD is the lowest, accounting for 0.15%. The TN load and TP load from rainfall-runoff pollution from April to September are higher than those in the rest of the months and the most polluted rainfall-runoff is in July.

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AUTHOR CONTRIBUTIONS

Minghui Zhang developed the methodology and software, validated the article, conducted a formal analysis and data curation, and wrote the original draft. Lin Wang conceptualized the whole article, wrote the review, edited the article, supervised the work, and conducted funding acquisition. Xuda Huang conducted investigation, brought resources, reviewed & edited the article, and administered the project. Zhonghua Yu brought resources, reviewed & edited the article, and administered the project.

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DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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